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QoE-aware Optimization of Video Stream Downlink Scheduling over LTE Networks using RNNs and Genetic Algorithm

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Abstract

Long Term Evolution (LTE) is the initial version of fourth-generation (4G) networks which provides ubiquitous broadband access. LTE supports multimedia Quality of Service (QoS) traffic with high data transfer speed, fast communication connectivity, and high security. Multimedia traffic over LTE networks is one of the highest percentages of mobile traffic and it has been growing rapidly in recent years. Our approach focuses on the development of Quality of Experience (QoE) aware optimization downlink scheduling video traffic flow. QoE is the overall acceptability of a service or application, as perceived subjectively by end users. In this work we aim to maximise QoE of video traffic streaming over LTE networks. This work introduces a novel integration framework between genetic algorithm (GA) and random neural networks (RNN) applied to QoE-aware optimization of video stream downlink scheduling. The proposed framework has been applied and evaluated using an open source simulation tool for LTE networks (LTE-Sim). A comparison between our framework and state-of-the-art LTE downlink scheduling algorithms (FLS, EXP-rule, and LOG-rule) has been done under different network conditions. Simulation results have shown that our scheduler can achieve better performance in terms of QoE (~10% increase), throughput and fairness.

Keywords: Video quality prediction; LTE; QoE; GA; RNN

1. Introduction

Transmission of video content over wireless communication will be the main contributor to future traffic in Internet applications. A recent study conducted by Cisco[1] indicates that global mobile data traffic grew by 66% in 2014, and mobile data traffic will grow at a compound annual growth rate (CAGR) of 57% between 2014 and 2019. Mobile video traffic represented approximately 50% or more of the world's mobile data traffic starting in 2014 and two-thirds of the mobile data traffic will be video by 2019. With the increasing demand for video-based applications, a better understanding of quality as perceived by end-users will become increasingly important. The service provider waits for customer complaints before taking action to improve the low QoS. According to an Accenture survey[2], approximately 90% of customers go to another provider instead of complaining about low-quality service.

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Consequently, it would be a useful tool if the service provider could continually measure the QoE and optimize the parameters values to improve the service quality in terms of MOS, fairness, throughput etc.

A recent study conducted by Telecoms[3] indicates that operators see video content streaming as one of the most lucrative LTE services. The Telecoms Intelligence Annual Industry Survey 2015 has shown approximately (75%) of respondents identified video content as one of the highest services enabled by LTE with the most revenue-generating potential. Therefore, a video traffic and users' preferences of video quality have been taken into account to design QoE-aware optimization of video stream scheduling in order to provide the satisfaction of end users (QoE). The proper design of the scheduling algorithms has become the main issue to obtain high-performance of data traffic over wireless networks. In particular, the main goal of this work is an optimum usage of available network resources in order to provide high-quality video transmission over LTE networks. This is related to the network ability to select optimal parameters and the appropriate scheduling algorithm to obtain the best QoS and to optimum capitalize of network capabilities. Scheduling algorithms can be formulated as optimization problems where the objective is to optimize a given parameters, such as bitrate, scheduling metric, queue delay or even bandwidth. From this perspective, we address the need for optimizing a scheduling algorithm aiming to maximize QoE when an available channel is shared among video traffic flows. While a few works exist in the field of QoE-aware network resource management, to the best of our knowledge, there is no framework proposal that applies GA with RNN theory in order to maximize QoE. The main contributions of this paper are:

(i) Optimizing the distribution of available network resources among network users is a target towards maximizing Mean Opinion Score (MOS)[4] and fairness.

(ii) Modeling of LTE downlink scheduling with RNN to learn complex non-linear mapping of QoE and GA to search for the global optimum through particular parametric space based on RNN model.

The rest of the paper is organized as follows. Section II presents an overview of downlink scheduling algorithms in LTE. Section III presents the fundamentals of LTE system, genetic algorithm, and random neural network. Section IV presents QoE-aware optimization proposed model, the data set generation, and simulation set-up. Section V concludes the paper and outlines the future directions of our research.

2. Scheduling Algorithms in LTE Networks

Packet scheduling algorithm or dynamic resource allocation is one of the most significant features in the wireless communication techniques since it is responsible for the distribution of available network resources among active users to meet Quality of Service (QoS) according to individual needs. The key function of the scheduling algorithms is providing fairness among users and maximizing the network performance. Broadcast of the data over LTE networks is organized by entities of time domain and frequency domain as physical resources. The Time Domain Packet Scheduling (TDPS) selects a subset of active users in current Transmission Time Interval (TTI) and Frequency Domain Packet Scheduling (FDPS) allocates Resource Blocks (RBs) to each user[5].

2.1. General Classification of Scheduling Strategies

Scheduling strategies are classified into several types as follows: (i) Channel insensitive Strategy, (ii) Channel sensitive without QoS-aware Strategy and (iii) Channel sensitive with QoS-aware Strategy. In LTE technology the major feature is applying channel sensitive scheduling strategy with QoS provisioning, and for this reason, we will focus to channel sensitive and QoS-aware strategy. In general, the scheduling strategy or resource allocation repeats every TTI and can be divided into two steps: firstly each user explores the quality of the signal and sends feedback of Channel Quality Indicator (CQI) of the signal status to the station (eNB). Then the eNB uses the information obtained by CQI for the allocation Resource decisions. Several scheduling algorithms targeting to various QoS-aware have been introduced in the literature as shown in Table I. However, resource allocation strategies aimed at maximizing subjective quality perception of end users (QoE), throughput and fairness have not received too much attention.

2.2. General Scheduling Metrics in LTE System

One of the key features of LTE is the scheduling algorithms or distributing available resources between active users. Table II shows most commonly scheduling metrics used for resource allocation in LTE system. Resources are allocated to each user (UE) depending on the comparison of resource block metrics (RB): the k^{th} RB is allocated to the j^{th} user if its metric $m^{j,k}$ is the biggest one accordingly, this user will serve first. The value of this metric can be determined according to the priority and performance requirement based on the following factors[5]:

- Status of transmission queues, based on the status of queues, the longest queue will have the highest metric.
- Channel Quality, based on the feedback of Channel Quality Indicator (CQI) value, the highest expected throughput will have the highest metric.
- Quality of Service (QoS), based on the QoS requirements, the lowest Quality Class Identifier (QCI) value will have the highest metric.
- Resource Allocation History, based on the past achieved performance, the lowest past throughput will have the highest metric.
- Buffer State, based on the buffer condition at the receiver side, the highest available space in the buffer will have the highest metric.

Table 1. scheduling algorithm based on QoS

Scheduling	Target	Key Aspects	Parameters
Proportional Fair (PF)[6]	Fairness & Max bitrate	Balancing between requirements on spectral efficiency & fairness	SINR & Throughput.
PSS/PF_{sch}[7]	Fairness & Max bitrate	Joint PSS at TDPS & PF_{sch} at FDPS structure.	SINR & Throughput.
M-LWDF[8]	Delay-Bounded	LWDF scheduler for bounded delay & PF for channel awareness.	SINR, D_{HOL}, Max Delay, Max PLR & Throughput.
EXP/PF[8]	Delay-Bounded	Exponential rule for bounded delay & PF for channel awareness.	SINR, D_{HOL}, Max Delay, Max PLR & Throughput.
LOG rule[9]	Delay-Bounded	Logarithm rule for bounded delay & PF for channel awareness.	SINR, D_{HOL}, Max Delay & Throughput.
EXP rule[9]	Delay-Bounded	Exponential rule for bounded delay & PF for channel awareness.	SINR, D_{HOL}, Max Delay & Throughput.
Frame Level Scheduler (FLS)[10]	Delay-Bounded	Double layer scheduler structure & Control law for resource pre-emption of real-time flows.	Max PLR & Queue Length.
Delay Prioritized Scheduling (DPS)[11]	Delay-Bounded	Prioritization of delay constrained flows. RBs upon meeting QoS requirement are allocated to the user with the highest priority.	SINR, D_{HOL}, Max Delay & Throughput.
Multi-QoS Aware Fair (MQAF)[12]	Max Bitrate	Grouping GRB & non-GBR, RB assigned to GBR users upon meeting GBR needs & spare resources left to non-GBR.	SINR & Throughput.
QoS Provide (QoSP)[13]	Max Bitrate	Priority: RBs upon meeting GBR requirement are allocated starting from the user with the highest priority.	SINR, D_{HOL} & Throughput.
CGTVTM[14]	Delay-Bounded & min bitrate	Exponential rule for bounded delay & virtual token mechanism for min guaranteed bitrate.	SINR, D_{HOL}& Max Delay.
QoE-aware[15]	Maximum QoE	consider a resource allocation scheme aimed at maximizing the overall average MOS.	MOS, Min Delay & Max Delay.

2.3. General Scheduling Metrics in LTE System

There are many parameters used to calculate the scheduling matrix, which is used to determine the priority of allocating network resources to active users. The most important of these parameters are as follows:

- The signal to interference plus noise ratio (SINR), it's a way to measure the quality of wireless connections in the wireless communication.
- Throughput, it's the data rates that are delivered to terminals in the wireless communication.
- Target delay, it's the maximum time which allows the pack to remain in the queue before transmit or deleted.
- Head of line delay, it's the delay of the first packet to be transmitted.
- Queue length, it's the length of the data in the queue before resource allocation.
- Quality of Experience (QoE) or perceived quality of the end user, it's the overall acceptability of an application or service as perceived by the end user.

Table 2. LTE Scheduling Metrics

Algorithm	Scheduling Matrix (SM)	Scheduling Parameters	Nomenclature
1. PF	$m_{i,k}^{PF} = d_k^i(t)/\overline{R^i}(t-1)$	$d_k^i(t) = \log[1 + SINR_k^i(t)]$	SINR: Signal-to-Interference-plus-Noise Ratio
2. M-LWDF	$m_{i,k}^{M-LWDF} = -\frac{\log \delta_i}{\tau_i} . D_{HOL,i} . m_{i,k}^{PF}$	D_{HOL}: Head of line packet delay	$m_{i,k}$: Generic metric of the i^{th} user on the k^{th} RB $D_{HOL,i}$: delay of the first packet to be transmitted by the i^{th} user
3. EXP/PF	$m_{i,k}^{EXP/PF} = exp\left(\frac{\alpha_i . D_{HOL,i} - x}{1+\sqrt{x}}\right) . m_{i,k}^{PF}$	$x = \frac{1}{N_{rt}} \sum_{i=1}^{N_{rt}} \alpha_i . D_{HOL,i}$	$R^i(t)$: Average throughput achieved by the i^{th} user
4. FLS	$m_{i,k}^{PF\ con\_flow} = d_k^i(t)/\overline{R^i}(t-1)$	Double-layer scheduler structure & Control flow	τ_i: Delay Threshold for the i^{th} user
5. EXP rule	$m_{i,k}^{EXPrule} = b_i exp\left(\frac{a_i . D_{HOL,i}}{c+\sqrt{x}}\right) . \Gamma_k^i$	$x = \frac{1}{N_{rt}} \sum_j D_{HOL,j}$	δ_i: Acceptable packet loss rate for the i^{th} user Γ_k^i: Spectral efficiency for the i^{th} user
6. LOG rule	$m_{i,k}^{LOGrule} = b_i \log(c + a_i D_{HOL,i}) . \Gamma_k^i$	ai, bi and c are tunable parameters.	$d_k^i(t)$: Expected data rate for the i^{th} user

3. The System Model and Neural Network

In this section, a more detailed description of the system and the intelligent learning models will be provided in the following subsections: (A) Summary of the LTE system, (B) Summary of Genetic Algorithm, (C) Random Neural Networks.

3.1. Summary of the LTE System

LTE was identified by the third generation partnership project (3GPP) as the preliminary version of the 4G wireless communication systems. The goal of LTE is to provide higher radio access data rates and low latency and to achieve great capacity and reliable high speed in mobile telephone networks. Furthermore, LTE guarantees enhanced spectrum flexibility and compatibility with other 3GPP radio access technologies. Also, the overall network architecture, the so-called system architecture evolution (SAE), has been improved. The LTE radio access is based on orthogonal frequency division multiplexing (OFDM) and provides a highly flexible bandwidth. Both frequency-division duplex (FDD) and time division duplex (TDD) multiple access techniques are supported. LTE uses MIMO operation and OFDM instead of CDMA over 3G. Applying MIMO and OFDM supported data rate up to 100 Mb/s download and 50 Mb/s upload. The QoS support is an important feature of the LTE[4]. These significant differences make LTE is 10 times faster than 3G. Although the presence of numerous protocols supports QoS, applying it in live LTE networks remains challenging due to channel characteristics, handoff support among a variety of networks, changing bit rates, bandwidth allocation propagation conditions and application types[16].

3.2. Summary of Genetic Algorithm

A genetic algorithm (GA) is a search method for solving both optimization problems that strike a remarkable balance between exploration and exploitation of search space based on a natural selection process that mimics biological evolution. GA relies mainly on Darwin's principle of eclecticism where passed optimum benefits through successive breeding operations and the strengthening of these qualities. These qualities have greatest ability to enter the breeding process, the production of offspring optimization, and repeating the cycle improves the genetic quality of the new generations[17].

3.3. Random Neural Networks

Random neural networks (RNNs) are mathematical models that combine features of both the classical ANN and of queuing models. They were introduced by Gelenbe[18] at the end of the eighties. RNNs have been efficiently used as learning tools in many applications and have shown high accuracy and more robust performance than ANNs. These models have many features that make them more appropriate for modeling the QoE of video stream. RNNs are composed of a set of interconnected neurons. These neurons exchange signals with each other and with the environment. These signals are transmitted immediately between neurons, or between a neuron and the environment. Each neuron is represented by a positive or negative integer one, whose value increases by one when it receives excitation spikes and decreases by one when an inhibition spike arrives. The spikes can originate either from outside the network or from another neuron within the network. Neurons whose excitation state is positive are allowed to send out spikes to either kind of neuron in the network. When a neuron receives a positive signal, either from another neuron or from the environment, its potential is increased by 1; conversely, if it receives a negative signal, its potential decreases by 1 if it was strictly positive, and it does not change if its value was 0. Similarly, when a neuron sends a signal, positive or negative, its potential decreases by 1; it was necessarily strictly positive since only excited neurons send signals[19].

4. Model and Simulation Set-up

4.1. Optimization Proposed Model

This work employs the integration of RNN with GA to maximize QoE of video traffic over LTE. The flowchart in Fig.1 illustrates the process of integration between RNN and GA to optimization scheduling algorithm of video streaming over LTE networks. The process initiates with the identification of the network system input parameters and their boundaries. The network system input parameters are composed of network parameters and application parameters. These control parameters are the targets (like send bitrate (SBR), scheduling matrices type (SM), and target delay) that the system is to respond for achieving a fitness function (like maximize QoE, throughput and fairness, minimize delay and packet loss rate).

The next stage includes the development of the GA population of the input network system parameters for use in the probabilistic-based optimal search followed by prediction function based on an RNN model. In the communication network system, the fitness function usually linked to the cost function of MOS. Once the output is available through the RNN prediction model, this output is passed to the cost function to calculate the newest value and compared to relevant previous outputs. The fitness requirements are updated from time to time according to the value of the cost function, at the same time a new generation of the population will be produced and gone through the same evaluation process of old generation. This process continues until achieving a certain condition or reached the maximum number of generations. The final population of the generation groups that has the highest cost is designated the final fitness (The winner)[20].

4.2. Global Searching by Genetic Algorithm

The input parameters of LTE network system are divided to control parameters and uncontrolled parameters. The control parameters such as SBR, SM, and Delay are targets to achieve maximal QoE. Uncontrolled parameters are any parameters not controlled by the system but have an effect on the network performance such as Speed and Users number (UE). In this optimization process, the outputs of the GA should be the optimal set of the controllable QoS parameters to maximize MOS. In general, the GA program works as the following steps:

A. To initialize a population, the size of populations was 100, which is a trade-off between an efficient searching process and the avoidance of premature convergence. The initial population was chosen randomly within the assigned input constraints, i.e. SBR from 128 kb/s to 880 kb/s, Scheduling Metric type from 1 to 6 as illustrated in Table II, target delay from 0.04 s to 0.1 s, Speed from 3 km/h to 120 km/h and Users from 10 to 30. All these parameters were converted from decimal to binary format using C++ code software.
B. To evaluate each chromosome by applying the RNN model and the cost function to the decoded sequences of the variables. The results were obtained for the entire population. They were compared to give the ranked fitness values.
C. To use the three genetic operators to alter the composition of the offspring in the next generation based on the pre-set probability values as follows:
   - Selection operator: The main idea of selection is to give preference to better individuals based on their fitness and allowing them to pass to the next generation. The ranked fitness values are determined by an objective function based on RNN model. A selection of a new population was made by the roulette wheel method as shown in Fig. 2. Solution “A” of 30% ratio has a higher probability of being selected because it occupies a larger section of the area while solution “B” of 10% ratio has a lesser chance of being selected. Therefore, chromosomes with higher fitness values occupy a larger block and will have a higher proportion to be in the new generation.
   - Crossover operator is one of the most important features that distinguish GA from other optimization techniques. Two individuals are chosen from the population using the wheel selection method, selecting random points along the strings of chosen individuals then exchange the values at these points as shown in

Fig. 3. The new offspring created from this mating leads to creating even better individuals of the new generation.

- Mutation operator is an overthrow in the one of the bits of the new individuals from 0 to 1 or vice versa. Its purpose is to maintain diversity within the population and prevent premature convergence as seen in Fig. 4.

D. Cyclic repetition of the above steps (B) and (C). The algorithm was stopped after a fixed number of iterations. This depended on the maximum number of generations.

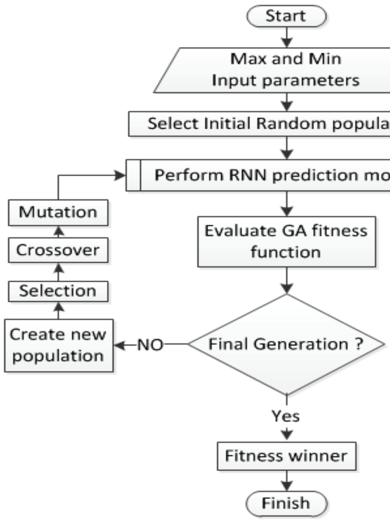

Fig. 1. Optimization schema based on RNN and GA.

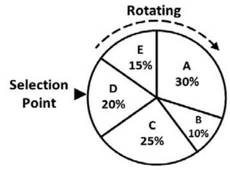

Fig. 2. Roulette wheel selection.

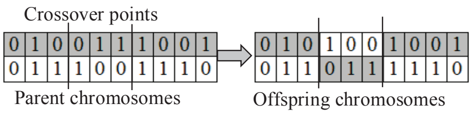

Fig. 3. Two-point crossover.

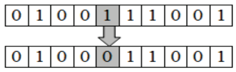

Fig. 4. Binary chromosomes mutation.

4.3. RNN prediction model

In identifying the input variables, we focused on defining the most significant parameters for QoE. Appropriate RNN architecture and a training algorithm were selected by MATLAB software[21] and C++ language. A four-layer feed-forward RNN model was used, consisting of five neurons in the input layer which correspond to the five chosen parameters (SBR, SM, Delay, Speed, and UE), two output neurons corresponding to MOS and fineness, and two hidden layers; each layer has eight neurons, as shown in Figure 5. The quality database obtained above was divided randomly into two parts: the first was used to train the models while the second one was used to test their accuracy. The RNN-based prediction model presented here was trained with a gradient descent (GD) training algorithm and tested using an untrained dataset.

4.4. Experiments

To create a degraded video database composed of sequences corresponding to different configurations of the selected parameters, the simulation scenario shown in Figure 6 was used. An open source framework to simulate LTE networks (LTE-Sim), mainly developed by G. Piro[5], was used to generate a video distortion database as follows: a realistic single-cell scenario was made which had a radius of 0.5 km, and the 19 cells in each cell, there are one eNodeB and between 10 and 30 user equipment (UEs). The UEs' movement traveling cells with one video flow were simulated with the random walk mobility model with a speed of 3 to 120 km/h. There are three sender nodes, one video source, one VoIP source and one best-effort source, as shown in Figure 6. The video traffic used is known as a trace-based application, which delivers packets that are based on the realistic video trace files. Five simulations were run for each number of users with three different scheduling algorithms[10] Frame level scheduler (FLS), Exponential rule (EXP-rule), and Logarithmic rule (LOG-rule) to calculate the average MOS and fairness. When the simulation is used to send video sequences from the source to the destination, every configuration with its defined input data must be mapped into the system composed of the network, the source, and the receiver. The destination stores the corresponding values of the parameters of the transmitted video sequence. Then, by running the simulation many times, we generated and stored a set of distorted video sequences with corresponding parameter values. Through the database that obtained above from LTE-Sim simulation we have trained our RNN model on available LTE scheduling Matrix so that it becomes able to predict the specific outputs of the network. Consequently, Genetic Algorithm (GA) creates new populations and evaluates their fitness by RNN model to find the optimal input parameters of the network system. This model was designed to obtain maximum MOS and best fairness of video traffic. However, it is possible to add different parameters like throughput, bandwidth, Packet Loss Rate (PLR), etc. based on network system requirements.

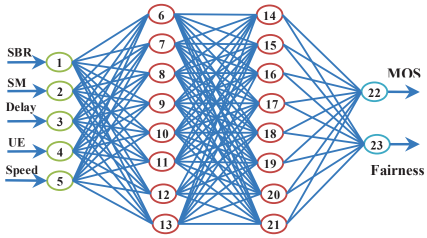

Fig. 5. The proposed RNN based

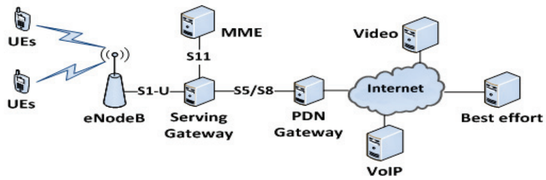

Fig. 6. LTE network topology.

5. Results and Discussion

In this section, we present and analyze the performance of our framework. The performance of RNN-GA framework has been analyzed and compared with the existing LTE scheduling algorithms (FLS, EXP rule, and LOG rule) in terms of QoE. The performance of FLS, EXP rule, LOG rule, and RNN-GA have been evaluated by varying the number of UEs (10 - 30), and the speed (3, 30, and 120 km/h) to real-time video flows. The comparison was based on the performance of the QoE of MOS and the fairness issues of video flows. The quality of received video data has been estimated computing the MOS between the transmitted and the received videos. MOS considers one of the key metrics for QoE evaluation in real-time video streaming systems. Figure 7 shows the MOS computed for the video streaming, as expected, the MOS decreases as the speed and users increase. However, the most important result we have obtained is that the proposed framework is able to provide the highest MOS in all operative conditions. Particularly, the proposed framework is able to guarantee an MOS gain up to about 3.5 in scenarios having up to 30 UEs with 3 km/h. According to ITU-T Recommendation P.910[22], the MOS score greater than or equal to 3.5 corresponds to satisfaction for all UEs with respect to FLS, LOG rule, and EXP rule schedulers. The achieved system throughput is the sum of the data rates that are delivered to all network active users that measured in bits per second. Figure 8 shows the throughput achieved for video flows with speed 3, 30, and 120km/h. It is easy to note that the throughput increases with the RNN-GA scheduling algorithm, due to the optimal choice of parameters by GA. In addition to the above, when designing a scheduling algorithm should take in account the expense of fairness, In other words, a scheduling algorithm should be fair in the sense that, in addition to guaranteeing a QoE-aware optimization, it is important to ensure that a fair manner distribution of resources to all active users, and do not allow to achieve good results for some users at the expense of others. The ranges index value between 0 and 1 of a given metric could be used suitably as a measure of fairness, the values closer to 1 the index of a metric is the fairer a discipline and vice versa. Figures 9a and 9b show that RNN-GA scheduler provides a slightly more fairness among state-of-the-art LTE downlink scheduling algorithms. This indicates that our RNN-GA model works best compared with other scheduling models that reported in[5].

6. Conclusion

The main goal of this work was to design a new QoE–aware optimization downlink scheduling algorithm of video streaming over LTE networks. The new optimization scheduling algorithm has been used based on genetic algorithm (GA) integrated with Random neural network (RNN) to identify optimal scheduling matrix (SM) with global optimal input parameters targeting maximizing QoE and fairness. This integration combines the ability of the GA for quick search of the optimal choice within the bounded parametric space, and that of RNN to learn complex nonlinear mapping for maximum QoE. Through the analysis of scheduling of performance that has been done in a complex scenario, it can be clearly seen that RNN-GA is able to obtain better MOS and fairness performance compared to FLS, EXP, and LOG schedulers. In conclusion, our QoE-aware optimization proposal framework is not only has the best performance in terms of QoE, but we could see that it is also the best in terms of the throughput and fairness also. Modeling of LTE uplink scheduling algorithms with RNN and GA is potentially one direction for the future research in this area. Another possible route is to apply different optimization algorithms like evolutionary algorithms which combine the advantages of an RNN with optimization algorithms.

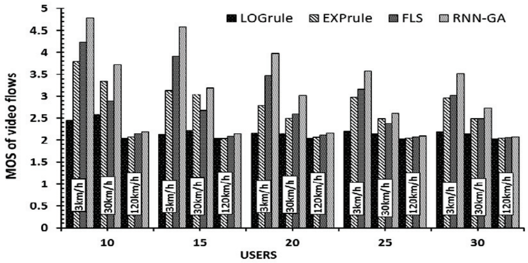

Fig. 7. MOS comparison with speeds 3, 30 and 120 km/h

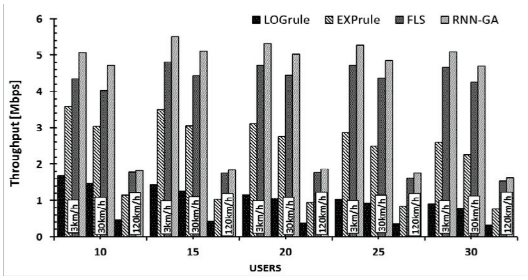

Fig. 8. Throughput of video flows with speeds 3, 30 and 120 km/h

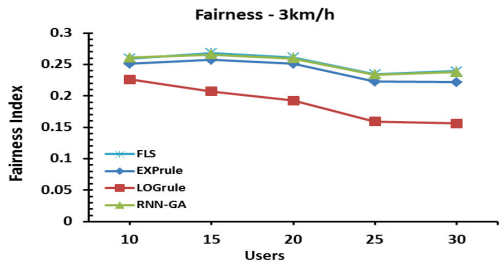

Fig. 9a. Fairness of video flows with speed 3 km/h

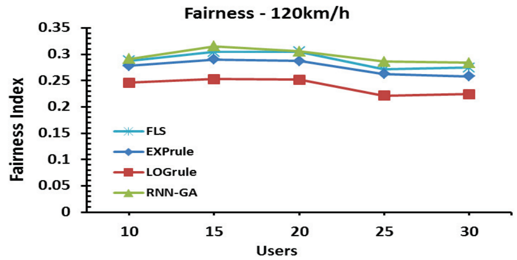

Fig. 9b. Fairness of video flows with speed 120 km/h

References

1. T. Cisco, "Cisco Visual Networking Index: Global Mobile Data Traffic Forecast Update, 2013–2018," Cisco Public Information, 2014.
2. Nokia white paper, "Quality of Experience (QoE) of mobile services: Can it be measured and improved?" 2004.
3. Scott. Bicheno, "Telecoms.com intelligence annual industry survey 2015," Telecoms.com, February. 2015.
4. I. Rec, P. 800.1, "Mean Opinion Score (MOS) Terminology," International Telecommunication Union, Geneva, 2006.
5. F. Capozzi, G. Piro, L. A. Grieco, G. Boggia and P. Camarda, "Downlink packet scheduling in LTE cellular networks: Key design issues and a survey," IEEE Communications Surveys & Tutorials, vol. 15, pp. 678-700, 2013.
6. C. Wengerter, J. Ohlhorst, V. Elbwart and A. G. Edler, "Fairness and throughput analysis for generalized proportional fair frequency scheduling in OFDMA," in IEEE Vehicular Technology Conference 2005, (VTC'05-Spring), pp. 1903-1907, 2005.
7. G. Monghal, K. I. Pedersen and P. Mogensen, "QoS oriented time and frequency domain packet schedulers for the UTRAN long term evolution," in IEEE Vehicular Technology Conference 2008, (VTC Spring '08), pp. 2532-2536, 2008.
8. R. Basukala, H. Ramli and K. Sandrasegaran, "Performance analysis of EXP/PF and M-LWDF in downlink 3GPP LTE system," in First Asian Himalayas International Conference on Internet 2009. (AH-ICI'09), pp. 1-5, 2009.
9. B. Sadiq, R. Madan and A. Sampath, "Downlink scheduling for multiclass traffic in LTE," EURASIP Journal on Wireless Communications and Networking, vol. 2009, pp. 14, 2009.
10. G. Piro, L. A. Grieco, G. Boggia, R. Fortuna and P. Camarda, "Two-level downlink scheduling for real-time multimedia services in LTE networks," IEEE Transactions on Multimedia, vol. 13, pp. 1052-1065, 2011.
11. K. Sandrasegaran, H. A. M. Ramli and R. Basukala, "Delay-prioritized scheduling (DPS) for real time traffic in 3GPP LTE system," in IEEE Wireless Communications and Networking Conference 2010 (WCNC'10), pp. 1-6, 2010.
12. Y. Zaki, T. Weerawardane, C. Görg and A. Timm-Giel, "Multi-QoS-aware fair scheduling for LTE," in IEEE Vehicular Technology Conference (VTC Spring'11), pp. 1-5, 2011.
13. D. N. Skoutas and A. N. Rouskas, "Scheduling with QoS provisioning in mobile broadband wireless systems," in European Wireless Conference 2010 (EWC'10), pp. 422-428, 2010.
14. M. Iturralde, A. Wei, T. A. Yahiya and A. Beylot, "Resource allocation for real time services using cooperative game theory and a virtual token mechanism in LTE networks," in IEEE Consumer Communications and Networking Conference (CCNC'12), pp. 879-883, 2012.
15. I. Taboada, F. Liberal, J. O. Fajardo and U. Ayesta, "QoE–aware optimization of multimedia flow scheduling," Computer Communication, vol. 36, pp. 1629-1638, 2013.
16. E. Dahlman, S. Parkvall, and J. Skold, "4G: LTE/LTE-Advanced for Mobile Broadband," Academic Press, 2013.
17. D. E. Goldberg and J. H. Holland, "Genetic algorithms and machine learning," Mach. Learning, vol. 3, pp. 95-99, 1988.
18. E. Gelenbe, "Random neural networks with negative and positive signals and product form solution," Neural Computation, vol. 1, pp. 502-510, 1989.
19. E. Gelenbe, "Stability of the random neural network model," Neural Computation, vol. 2, pp. 239-247, 1990.
20. D. Whitley, T. Starkweather and C. Bogart, "Genetic algorithms and neural networks: Optimizing connections and connectivity," Parallel Computing, vol. 14, pp. 347-361, 1990.
21. H. Abdelbaki, "Random neural network simulator (rnnsim) v.2," Free Simulator Available at http://www.mathworks.co.uk/matlabcentral/file exchange/ authors/1164/mathworks.com/pub/contrib/v5/nnet/rnnsimv2, 1999.
22. P. ITU-T Recommendation, "Subjective video quality assessment methods for multimedia applications," 1999.